

Walker D, Forsythe N, Parkin G, Gowing J. [Filling the observational void: scientific value and quantitative validation of hydrometeorological data from a community-based monitoring programme](#). *Journal of Hydrology* 2016

DOI: <http://dx.doi.org/10.1016/j.jhydrol.2016.04.062>

Copyright:

© 2016 The Authors. Published by Elsevier B.V. Open Access funded by Natural Environment Research Council under a Creative Commons [license](#)

Date deposited:

10/05/2016



This work is licensed under a [Creative Commons Attribution 4.0 International License](#)

Filling the observational void: Scientific value and quantitative validation of hydrometeorological data from a community-based monitoring programme

David Walker¹, Nathan Forsythe¹, Geoff Parkin¹, John Gowing²

1. School of Civil Engineering & Geosciences, Newcastle University, Newcastle upon Tyne, NE1 7RU, United Kingdom

2. School of Agriculture, Food & Rural Development, Newcastle University, Newcastle upon Tyne, NE1 7RU, United Kingdom

Correspondence to: d.w.walker1@newcastle.ac.uk

Abstract

This study shows how community-based hydrometeorological monitoring programmes can provide reliable high-quality measurements comparable to formal observations. Time series of daily rainfall, river stage and groundwater levels obtained by a local community in Dangila *woreda*, northwest Ethiopia, have passed accepted quality control standards and have been statistically validated against formal sources. In a region of low-density and declining formal hydrometeorological monitoring networks, a situation shared by much of the developing world, community-based monitoring can fill the observational void providing improved spatial and temporal characterisation of rainfall, river flow and groundwater levels. Such time series data are invaluable in water resource assessment and management, particularly where, as shown here, gridded rainfall datasets provide gross under or over estimations of rainfall and where groundwater level data are non-existent. Discussions with the local community during workshops held at the setup of the monitoring programme and since have demonstrated that the community have become engaged in the project and have benefited from a greater hydrological knowledge and sense of ownership of their resources. This increased understanding and empowerment is at the relevant scale required for effective community-based participatory management of shallow groundwater and river catchments.

Keywords

Citizen science; Hydrometeorology; Local data gaps; Quantitative validation; Water resource assessment; Ethiopia

1.1 Introduction

Continuous time series of rainfall, river flow and groundwater level vary in their availability. For many areas of, particularly the developing, world, such data is patchy or non-existent. Unfortunately, the areas of greatest data scarcity typically coincide with areas that suffer the greatest impacts from adverse hydrological conditions where more data could be used to better assess the current situation and to forecast future scenarios allowing for better mitigation and adaptation strategies. The importance of quantitative information on the rainfall which controls spatially and temporally variable water resources and of measurements of the surface/groundwater resources themselves is not in doubt (Bonsor and MacDonald, 2011; Conway et al., 2009; Washington et al., 2006). Satellite and reanalysis rainfall products are often promoted as the solution to low-density gauge networks, however, the greatest accuracy of such products is achieved in areas with abundant ground observation data to aid calibration (Dinku et al., 2008; Fekete et al., 2004; Symeonakis et al., 2009). What's more, the necessary spatial averaging means spatial resolution is commonly insufficient for smaller than regional scale hydrological and hydrogeological studies. Datasets at the relevant scale to inform local resource management strategies are increasingly being obtained by local communities providing a low-cost and highly useful source of hydrometeorological time series data where they would be otherwise unavailable (Gomani et al., 2010; Liu et al., 2008). The numerous additional benefits of such community-based monitoring programmes include the engagement and empowerment of local communities in their own water resources (Buytaert et al., 2014; Conrad and Hilchey, 2011). A recent editorial in *Nature* discussing the rise of "citizen science" in various fields states that data quality is the prime concern of critics (Nature, 2015). The majority of the literature presenting community-based monitoring programmes has sought to detail the benefits brought to the community though few (if any) papers have attempted to quantitatively validate the collected data in a statistical manner akin to the abundant literature validating remote sensing products against ground observations. It will be determined here whether community-based monitoring can provide data which can be satisfactorily validated against formal sources to provide improved spatial and temporal resolution, and whether it can supply reliable hydrogeological data where there are no formal alternatives. As formal monitoring networks continue to decline in many parts of the world, we determine if community-based monitoring programmes can be a viable complement.

1.2 Sub-Saharan Africa context

Rain gauge distribution across sub-Saharan Africa (SSA) is sparse, particularly in comparison with Europe, North America and South Asia. There are 1152 World Meteorological Organization (WMO) World Weather Watch stations in Africa at an average station density of just one per 26,000 km², 8 times lower than the WMO minimum recommended level (Washington et al., 2006). Fig. 1 shows the network of WMO stations clearly indicating the sparsity of stations in Africa and their uneven distribution resulting in substantial

areas going unmonitored. Within SSA, rain gauge densities are highest in coastal West and Southern Africa, and the East Africa Highlands of Kenya and Uganda, whereas areas of greater aridity are underrepresented. Furthermore, it is widely reported that rain gauge networks in SSA are in decline as weather services make cut backs (Maidment et al., 2014; Nicholson, 2001; Washington et al., 2004). Willmott et al. (1994) report a peak in African rain gauge density occurring in the 1950s and a sharp decline after 1970. South Africa has generally been commended for its relative abundance of rain gauges although Pegram and Bardossy (2013) report that even South African rain gauge records are dying off; after mid-2000 they found that out of the 279 gauges in the 5 regions only 180 survived until 2008. A more extreme example is Angola which had over 500 meteorological stations as a Portuguese colony which were all but destroyed during four decades of civil war until a government rebuilding programme had increased the number to eight by 2007 (Cain, 2015).

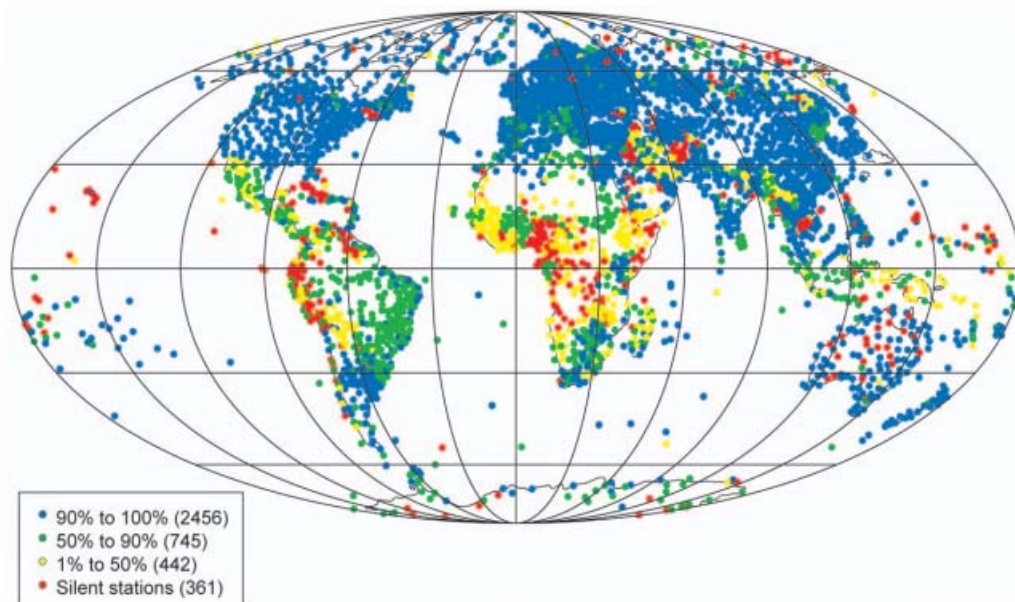


Fig. 1. The global network of World Weather Watch stations colour-coded to show reporting rates (WMO, 2003).

River flow monitoring networks in SSA are unfortunately experiencing a similar decline to meteorological monitoring networks. Monitoring stations globally have been decreasing in number over the last few decades. Tourian et al. (2013) note that among the 8424 identified gauging stations in the Global Runoff Data Center (GRDC) database only 40% of stations provide discharge data after 2003. Many of these monitoring stations going offline were located in SSA. The requirement to reverse the trend of decreasing hydrological monitoring is a widely held view (Kundzewicz, 1997; Owor et al., 2009; Taylor et al., 2009).

Even so, surface water is densely monitored in comparison with groundwater. There is general agreement that a better understanding of the shallow hydrogeology of SSA from the point of view of potential agricultural use is a necessity (Evans et al., 2012; Giordano, 2006; Namara et al., 2011; Pavelic et al., 2013).

Lapworth et al. (2013) state the issue succinctly; “Ideally, a thorough quantitative understanding of aquifer properties and recharge mechanisms under a variety of climate, land use and geological environments is required to confidently assess current groundwater availability, and forecast future availability under different scenarios”. A recent review of groundwater conditions in 15 SSA countries (Pavelic et al., 2012) concluded that: “Quantitative information on aquifer characteristics, groundwater recharge rates, flow regimes, quality controls and use is still rather patchy”.

Invariably simultaneously reported alongside comments on the need for greater understanding of SSA hydrogeology is the dearth of observations of groundwater systems, in particular sustained time series data (ATA, 2013; Calow et al., 2009; MacDonald et al., 2009; Martin and Van De Giesen, 2005; Taylor et al., 2009). The situation with groundwater data is different to the aforementioned decreasing meteorological and hydrological time series data because there have never been many monitoring systems in place. For example; considering the hydrogeology atlas of the SADC region (the Southern African Development Community which includes fifteen member states south of and inclusive of the Democratic Republic of Congo and Tanzania), Robins et al. (2006) report that only six of the member states (Lesotho, Mauritius, Namibia, South Africa, Swaziland and Zimbabwe) have formal monitoring networks involving water level and some type of water quality measurements. In the remaining countries sporadic measurement occurs though in an ad hoc fashion with little or no data reaching the national groundwater authority. This issue is not restricted to southern Africa as Martin and Van De Giesen (2005) report that the only data on shallow aquifers in Ghana and Burkina Faso is the total number of wells in a region while even production figures for small formalised piped groundwater supplies are not recorded. Dapaah-Siakwan and Gyau-Boakye (2000) who conducted broad-scale hydrogeological research in this region of West Africa chose to ignore shallow aquifers altogether because: “Even though many hand-dug wells have been constructed in various hydrogeologic formations (a total of about 60,000 as of March 1998; Ministry of Works and Housing, 1998), these were not taken into consideration in the analyses for this paper due to the dearth of data from these sources.” The limited groundwater data available in SSA is almost exclusively from deep abstraction boreholes, however, shallow groundwater is the resource which is accessible and exploited by the majority of rural communities via hand dug wells.

1.3 Community-based monitoring

It is increasingly advocated that community involvement should be strongly supported by the scientific community to improve links between science and local level planning policy (Ridder and Pahl-Wostl, 2005). While there are an increasing number of published works on stakeholder participation in environmental decision making, there are few concerning a participatory approach in quantitative environmental monitoring. The potential benefits of community-based monitoring are listed by Conrad and Hilchey (2011), compiled from an extensive literature review across a variety of fields, and include:

- Increasing environmental democracy (sharing of information).
- Scientific literacy (Broader community/public education).
- Social capital (volunteer engagement, agency connection, leadership building, problem-solving and identification of resources).
- Citizen inclusion in local issues.
- Data provided at no cost to government.
- Ecosystems being monitored that otherwise would not.
- Government desire to be more inclusive is met.
- Support/drive proactive changes to policy and legislation.
- Can provide an early warning/detection system.

Published studies of data collection from non-specialists, often termed “citizen science”, commonly involve the collection of “snapshots” of, for example; wildlife, soil type, or plants (Rossiter et al., 2015; Roy et al., 2012; Vianna et al., 2014). Monitoring of bird populations in programmes such as eBird (Sullivan et al., 2009), where several million species/date/location records are added monthly from around the world and believed to be the largest citizen science project in existence (Hochachka et al., 2012), are the only known studies where time series data is collected by non-specialists though the data are not necessarily gathered at regular times from the same locations. These momentary observations are less useful for most hydrological applications where complete time series of transient data are required. The theory and practice of citizen science in hydrology and water resources management has emerged mainly through experiences in developed countries in response to growing environmental activism. To date its scope is limited and there are only a few published examples within the hydrology and water resources literature of successfully implemented community-based monitoring programmes:

The APWELL project, instigated in the 1990s, developed participatory monitoring including 230 rain gauges and 2100 observation wells across 370 villages in the most drought-prone region of Andhra Pradesh, India. The project provided farmers with the necessary knowledge, data and skills to understand and manage their groundwater resource. The outcome was more efficient groundwater use, increased crop yield, and poverty reduction (Garduño and Foster, 2010; Garduño et al., 2009).

Gomani et al. (2010) detail an “integrated participatory approach” in setting up a monitoring network in a large (2780 km²) catchment in Tanzania as part of a project with an overall aim of assessing climate change impacts and land use options. The approach aimed to assimilate local and expert knowledge with some voluntary monitoring by the community including weather, river flow and groundwater measurements.

A smaller scale community-based monitoring programme in South Africa with the overall objective of watershed management for the increase of food production and improving rural livelihoods is detailed by

Kongo et al. (2010). This monitoring network was extremely equipment intensive and involved monitoring weather, river flow, deep and shallow groundwater, sediment load, overland flow, soil moisture and crop transpiration. It is claimed that the participatory aspect led to an appreciation of the research which sustained the goodwill of the community to safeguard the instruments and structures comprising the network. It is stressed that there is always a process to be followed when engaging stakeholders which needs to be based on trust, honesty and friendship.

Buytaert et al. (2014) present case studies detailing the benefits of community involvement in hydrological issues from Peru; identifying the hydrological impacts of land use change on ecosystems in remote upland areas beyond the range of formal monitoring networks, from Ethiopia; engaging farmers to rehabilitate gullies following soil erosion caused by poorly implemented land management practices, from Nepal; where communities have taken the lead in water sharing arrangements in an arid region, and from Kyrgyzstan; where water users associations (WUAs) are being set up who are installing monitoring schemes to replace those which died out at the end of the Soviet period.

The few other published case studies of water resource community-based monitoring programmes generally concern monitoring of water quality for various applications. They include; water quality monitoring in rural Mexico for public health where no professional assessments exist (Burgos et al., 2013); for monitoring river sediment load and nutrient contamination to assess the impact of soil erosion in a remote area of Mindanao, the Philippines (Deutsch et al., 2005), and; biological measurements (faecal coliform levels and macroinvertebrate indices) for protection of aquatic habitats in Georgia, USA (Conners et al., 2001).

This paper presents a case study of a community-based monitoring programme in Ethiopia and aims to show that community measured hydrometeorological data can pass strict published quality control procedures. Such data can be validated against formal sources proving that the data is reliable, of high quality, and can offer improved spatial and temporal resolution over formal ground observation and gridded datasets. To our knowledge there are no other published examples of attempts to rigorously validate data from community-based monitoring programmes.

2. Project context

2.1 AMGRAF research project

The AMGRAF (Adaptive Management of shallow GRoundwater for small-scale irrigation and poverty alleviation in sub-Saharan AFrica) research project commenced in 2013 with the overarching aim of establishing whether development of shallow groundwater resources for small-scale irrigation (and other purposes) can be used sustainably to alleviate poverty in SSA. The first field site selected was Dangila

woreda in northwest Ethiopia; an area identified by the Ethiopian ATA (Agricultural Transformation Agency) for an increase in irrigated agriculture. Further information on the AMGRAF research project can be found in the Supplementary Material.

2.2 Study area

Dangila *woreda* lies approximately 70 km southwest of Bahir Dar within the Amhara Region of northwest Ethiopia (Fig. 2). The *woreda* has an area of approximately 900 km² and a population of around 160,000, of which 132,000 are rural (CSA, 2008). Most of the 28,000 urban population reside within Dangila town east of centre of the *woreda* on the Addis Ababa – Bahir Dar road.

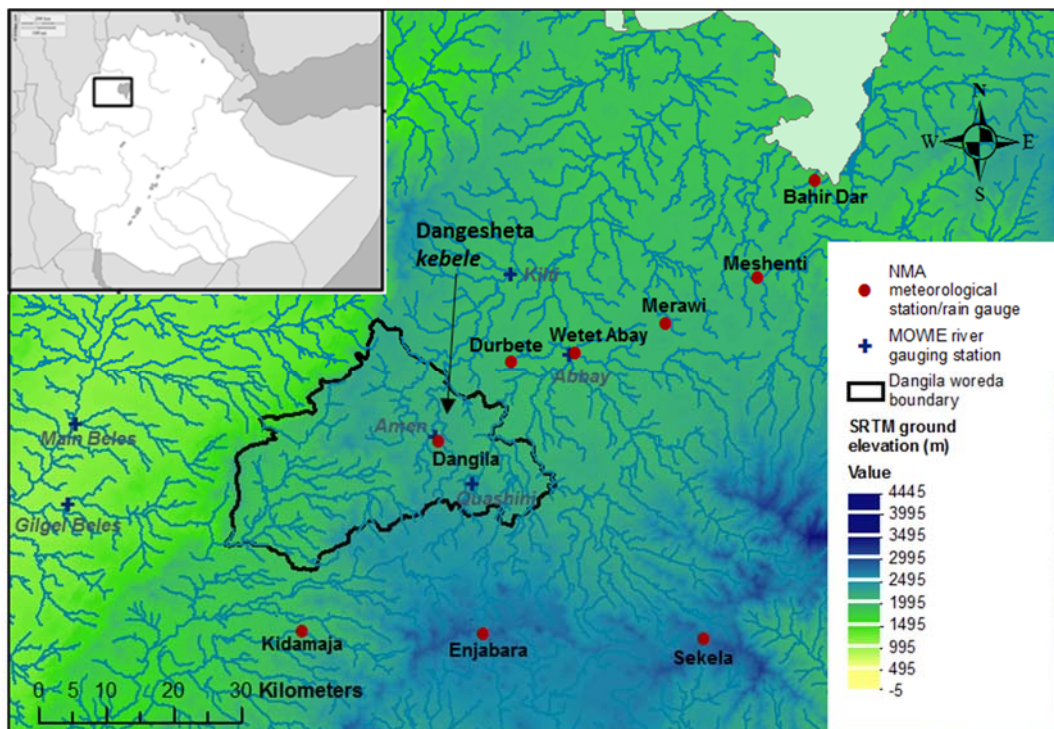


Fig. 2. Location map of the study area in the Amhara region of Ethiopia. Map shows formal rain gauges and river gauges near to Dangila *woreda*. Lake Tana is visible at the top of the map.

Elevation ranges from around 1600 m in the southwest to 2400 m in a central hilly belt, dropping again in the east, which includes Dangila town, to around 2100 m. West of the central hills is a relatively flat basin which drains to the Beles, a tributary of the Blue Nile. The east of the *woreda* drains via the Gilgel Abbay river into Lake Tana. Much of the *woreda*, including Dangesheta *kebele*, is formed of low hills and expansive floodplains. Floodplains are utilised as pasture throughout the year whereas crops and dwellings occupy the adjacent slopes. Rainfed agriculture predominates with little irrigation other than small household plots. The geology consists of Cenozoic basalts overlain by weathered regolith.

The climate is moist subtropical with little annual temperature variation though high diurnal variation. A median annual daily maximum temperature of 25 °C and minimum of 9 °C have been measured at the

National Meteorological Agency (NMA) weather station in Dangila. The median annual total rainfall is 1628 mm, 91 % of which falls during May to October.

2.3 Dangesheta monitoring network

The community-based monitoring programme was initiated in February 2014. The community were consulted and involved in siting the rain and river gauges and identifying the wells to be monitored (Figs. 3 and 4). Hydrologically suitable areas were identified, i.e. narrow channels and valleys for the river gauges where river stage fluctuations would be most pronounced and open areas with no overhead obstructions for the rain gauge. Certain locations were excluded for being too open where the community expressed concern over the security of the equipment. Ultimately the rain gauge was situated within the smallholding of the community member who would monitor the gauge. The monitored wells were chosen to provide a transect from close to the river and floodplain up towards a watershed boundary that would include successful wells with perennial supply and also unreliable seasonal wells. Another influence on monitoring well selection was the route that could be taken by the community member who would measure well level which leads in a broad circle from his house to his place of work (see Fig. 3).



Fig. 3. Locations of monitoring points (close to arrowhead in Fig. 2); MW = monitoring well, DSC = Dangesheta Service Cooperative, DAO = Dangesheta Agricultural Office. (Image source: Google earth; Imagery ©2015 DigitalGlobe).

The five monitoring wells are manually dipped every two days with a dip meter and the rain gauge is measured daily at 9am by reading the level of the internal graduated cylinder. The river gauges are monitored daily at 6am and 6pm by reading the river stage from the permanently installed gauge boards. Hard copy records of measurements are provided by community monitors on a monthly basis to the Dangila *woreda* office, where they are transferred to an Excel spreadsheet and forwarded to the research team. Further information on the monitoring network can be found in the Supplementary Material.



Fig. 4. Photographs of (left to right) the Kilti river gauge, the rain gauge, and measuring groundwater level at monitoring well MW5.

3. Data analysis methods

3.1 Sources of error

Potential errors in rainfall measurements can broadly be divided into two categories; sampling error and observational error. Sampling error results from spatial and temporal variability of rainfall. Sampling error increases with increased rainfall and decreases with increased gauge density and duration of rainfall event (Huff, 1970). Therefore, warmer regions where convective storms of high-intensity and short duration are common will see the greatest errors, particularly where rain gauge density is low (the Ethiopian Highlands fit this category). Observational error can be due to inaccurate measurements on individual days arising through observer errors, either during measurement or transcription. Detecting such errors is problematic because the skewed distribution of daily rainfall quantities signifies that in all but the most extreme cases a suspect measurement has a considerable likelihood of being correct (New et al., 2001). Measurement biases arise through gauge undercatch caused mostly by wind turbulence around a gauge though splash and evaporation can also have an effect (Legates and Willmott, 1990; New et al., 2001; Peterson et al., 1998).

The sources of error presented above are similarly applicable to river stage and groundwater level measurements. Biases can arise from taking measurements relative to poorly chosen reference points or due to equipment maintenance issues. Other observational errors which may be more likely to result from measurements by non-professionals include family or work commitments necessitating adjustments to observation time or a temporary change in observer.

3.2 Quality control

The quality control procedures of WMO, as presented in their “Guide to climatological practices”, have been followed in order to verify whether a reported data value is representative of what was intended to be measured and has not been contaminated by unrelated factors (WMO, 2011). Checks recommended by WMO comprise:

Format tests, e.g. impossible dates or words in numeric fields, typically caused by transcription errors.

Completeness tests, e.g. missing data which may or may not be important; a missing daily rainfall total during a wet period could have a significant effect on the monthly rainfall total whereas a single missing groundwater level measurement would not be crucial.

Consistency tests, further divided into four types of check; internal consistency checks, e.g. do maximum measurements exceed minimum or is wind direction between 0° and 360° (such tests are less applicable for this community data); temporal consistency checks, where the amount of change with prior and subsequent values is not greater than might be expected for the given time interval; spatial consistency checks, comparing observations with what would be expected based on observations from neighbouring locations; and summarisation consistency checks, e.g. do annual rainfall totals equal the sum of monthly and daily totals (this is less applicable for the community data where only daily measurements are received).

Tolerance tests, which set upper and lower limits on possible values with recourse to historical values or via spatial interpolation methods.

Similar to temporal and spatial consistency checks, care must be taken with tolerance tests to avoid excluding correct and particularly informative extreme values, such as happened with the Boscastle flood of 2004 in Cornwall, UK and the Great Storm of 1987 in southeast England when seemingly anomalous measurements could have improved forecasts to provide more warning of what became disastrous weather events (Golding et al., 2005; Woodroffe, 1988).

Considering the community data received in this case study, the initial screening procedure would reveal any gross errors, which may simply be typographical errors revealed by format and consistency tests, or extended gaps in the measurements revealed by completeness tests. Errors were revealed by this visual inspection including; received spreadsheets often had a mixture of English and Amharic characters which were not recognised by all computers, commas were often used in place of decimal points or spaces were present either side of decimal points, and there were occasional errors in the conversion from the Ethiopian to the Gregorian/Western calendar. Such errors were simple to rectify.

An additional quality control procedure is the double mass check which involves plotting the cumulative data of one station against the cumulative data of another nearby station. If the data records are consistent, a straight line is obtained. Data from stream flow gauges can be compared with data for other flow gauges in the same general area, and, similarly, data for rainfall gauges can be compared. Where an inconsistency is observed, such as a break in the slope of the line, an investigation into the cause should

be performed. Relocation of weather stations and dam constructions are examples of causes of such breaks in slope in rainfall and river flow data respectively (O'Donnell, 2012).

3.3 Validation of hydrometeorological data

There is much published literature which aims to validate alternative sources of rainfall measurements against ground observations from formal institutions (Ebert et al., 2007; Nicholson et al., 2003; Robinson et al., 2000; Wolff et al., 2005). The validation methodologies used are similar and consist of statistical comparisons typically evaluating correlation coefficient, error and bias. The alternative rainfall sources comprise satellite and reanalysis products. Specific examples covering Ethiopia include validation of different gridded rainfall datasets by Dinku et al. (2007) and Dinku et al. (2008). Published literature concerning validation of river flow and groundwater level data generally compares modelling simulations to observations (Beven, 1993; Motovilov et al., 1999; Refsgaard and Knudsen, 1996). No examples have been found in the literature of validation of data from community-based monitoring.

For this study, the community and formal data were compared using the Pearson correlation coefficient (PCC) and bias. PCC is the typical standard (including in all the studies cited in the previous paragraph) used to validate data from an alternative source against a formal source: a negative or low value indicating poor performance and questionable validity. However, because PCC simply measures the strength of the linear relationship between the datasets, a high PCC would result from a match in the structure of the data even if absolute values varied significantly. Therefore, bias is also computed to determine whether variation is systematic and could therefore be reduced with bias correction, or is due to random error. High seasonal variation between absolute measurements mean bias is a more useful descriptive indicator than other methods of calculating error such as mean error and RMS error. Gridded datasets have been evaluated using the same methodology in order to compare their performance with that of the community data.

$$PCC = \frac{N \sum C.F - (\sum C).(\sum F)}{\sqrt{(N \sum C^2 - (\sum C)^2). (N \sum F^2 - (\sum F)^2)}}$$

$$Bias = \frac{\sum C}{\sum F}$$

C = community monitored data or gridded data set
 F = formal ground observation data
 N = number of data pairs

The seasonality of the climate in this region means high correlations would be expected during the long dry season when little to no rainfall occurs and surface/groundwater levels are relatively static. Therefore, statistical comparisons were separately conducted for the wet season onset (May-June), wet season peak (July-August), wet season retreat (September-October), and the dry season (November-April), as well as for the full time series.

3.4 Behavioural differences in data

It is important to note that the formal and the community monitoring locations are not immediately adjacent and, as such, near-perfect correlations and zero bias are not expected. Variations in groundwater and river levels and in rainfall due to geographic position provide insights into local hydrogeology, hydrology and meteorology and the lower PCC derived from such variations does not call for rejection of data as long as the quality control procedures are passed. What's more, seemingly extreme values should not always cause the rejection of data during the quality control process but should be investigated properly. Local knowledge gained through field visits combined with anecdotal evidence from contacts in the area means extreme observations highlighted for rejection during tolerance tests may be correctly incorporated and are highly valued.

4. Rainfall

4.1 Formal ground observations

Rainfall data in Ethiopia is collected by the NMA. The density of rain gauges is low, as can be seen in Fig. 2, with only one rain gauge within 900 km² Dangila *woreda* and only an additional eight within a surrounding area of 5000 km². All the rain gauges outside of the *woreda*, particularly those to the south, lie at significantly different altitudes to Dangila *woreda*. In addition, the rain gauges to the northeast of the *woreda* lie along a straight line; the Dangila to Bahir Dar highway, which leads to unconfident extrapolation of rainfall data either side of the highway via methods such as Kriging or Thiessen polygons. Rainfall data has been collected for the nine rain gauges shown in Fig. 2 with the available dataset varying in length. Dangila is the closest NMA rain gauge to Dangesheta at 5.7 km distant to the south and at approximately the same altitude (~11 m difference). The Dangila rainfall record is the third longest (since 1987) but more importantly is the most complete while all other rain gauges have significant data gaps, often for a year or more. For these reasons of proximity and completeness, the Dangila rainfall record is used to evaluate the performance of the alternative rainfall sources (see Supplementary Material for further information substantiating the use of Dangila data for validation purposes).

4.2 Community data

At the time of writing, 18-months of data were available; March 2014 to October 2015, which span two wet seasons. The wet season is pronounced with approximately 85 % of rainfall recorded between May and October. However, the wet season of 2014 was atypical in that it started earlier, ended later, and had a less pronounced peak in July and August compared to historical records from the NMA for all nearby rain gauges. A double mass check conducted for rainfall from the community-based monitoring programme

against Dangila NMA confirms a reliable record (Fig. 5); based on double mass checks it appears more reliable than records from most of the alternative formal rain gauges.

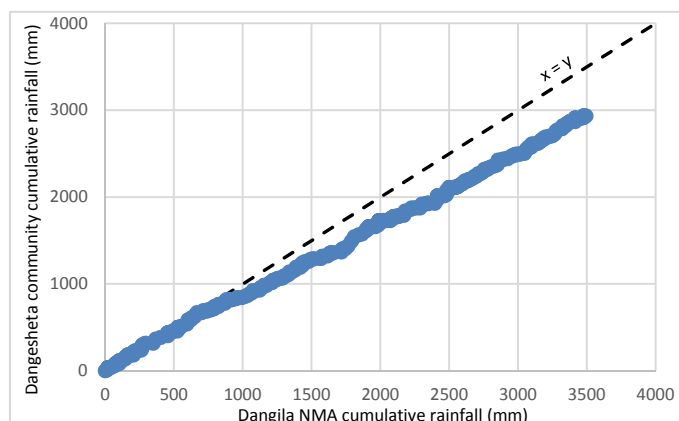


Fig. 5. Double mass check of rainfall for Dangila NMA with Dangesheta community showing a good linear relationships indicating a consistent record. Note that a good record is considered to be a straight line and not necessarily $x=y$.

Closer to the community rain gauge than the NMA formal rain gauge is an electronic automatic weather station, which is 960 m to the north beside the Dangesheta Agricultural Office (DAO on the map in Fig. 3) and at approximately the same altitude (~14 m difference). Installed by Bahir Dar University in March 2015, the electronic weather station incorporates a tipping bucket rain gauge, though unfortunately it stopped recording during the peak of the wet season leading to limited data with which to conduct comparisons.

4.3 Gridded datasets

The gridded remote-sensing and reanalysis rainfall datasets that have been considered are TRMM, ERA-Interim, NASA MERRA, JRA-55 and NCEP (see Supplementary Material). The spatial resolution of these gridded datasets varies from $0.25^\circ \times 0.25^\circ$ (TRMM) to $1.25^\circ \times 1.25^\circ$ (JRA-55) though this coarsest dataset provides the longest time series; since 1958. Such large grid squares over this region of Ethiopia necessarily comprise large altitudinal ranges, often of several thousand metres, and where multiple NMA rain gauges are present within a grid square the observed variations in rainfall totals can be very high.

4.4 Performance of alternative rainfall sources

Spatial consistency testing conducted as part of the quality control procedure involved plotting daily rainfall totals from Dangila NMA, Dangesheta community, and Dangesheta electronic rain gauges. The plots were very similar but with a slight shift in the peaks. It was immediately apparent that there had been an error in conversion from the Ethiopian to the Gregorian/Western calendar and when the

community rainfall time series was shifted by a day the peaks matched. Further investigation of rainfall data from the electronic rain gauge revealed that daily totals were summed from a 24-hour period spanning midnight to midnight. When the totals were recalculated for a 9 am to 9 am period, as per the formal and community measurements, the timing of peaks from all three datasets were in agreement. Values for the tolerance tests could be taken from the extensive formal rainfall datasets from the nine nearby rain gauges which were also used for consistency testing. All community rainfall data passed quality control testing.

Before correlating daily rainfall from the community gauge with the formal source, it was necessary to determine what PCC could be considered good performance. By correlating rainfall from the other nearby NMA rain gauges with that from Dangila, variations in PCC would show the degree of spatial and temporal variation in rainfall. The PCC was calculated using as long a time series as available for each rain gauge; the results are presented in Fig. 6a. As would be expected, the PCC increases as distance from the Dangila rain gauge decreases because error due to spatial and temporal variation lessens. The trendline is projected to the distance of the community rain gauge (5.7 km) and it can thus be stated that a PCC below this line (less than approximately 0.68) likely includes a degree of observational error.

Because the community data is available only from March 2014, the same period was used to evaluate the relative performance of the gridded datasets. JRA-55 and NCEP are excluded because the data were not available for this evaluation period. Where multiple seasons have occurred, i.e. wet season peak in 2014 and 2015, the mean PCC is taken; nowhere was it necessary to take means of markedly different values (Fig. 6b).

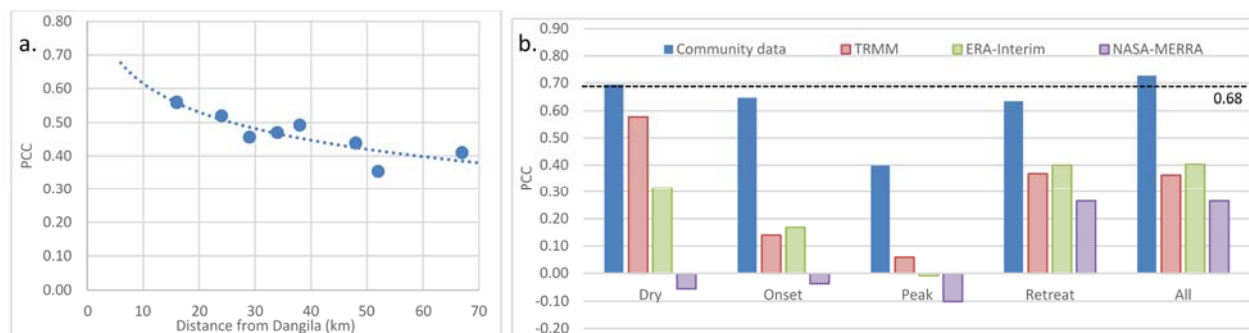


Fig. 6. Variation with distance of Pearson correlation coefficient (PCC) between daily rainfall from Dangila NMA rain gauge and other NMA rain gauges close to Dangila worda (a). Pearson correlation coefficient (PCC) between daily rainfall from Dangila NMA rain gauge and alternative sources (b).

Immediately apparent from Fig. 6b is that the community data outperforms the gridded datasets for all seasons. Localised short-lived storm events leading to high spatial and temporal variability are proposed for the reason behind the poor correlation of all alternative sources of rainfall data during the wet season peak. When all the data is considered (the far right of the graph), the PCC of 0.73 for the community data

is greater than the value predicted in Fig. 6a and the discrepancies with the formal dataset can therefore be considered sampling rather than observational error. Because they are just 900 m apart, it would be expected that the community rain gauge and the electronic rain gauge would correlate better than the dataset pairs presented in Fig. 6b; indeed the calculated PCC is 0.84.

Analysis of bias is presented in Fig. 7a. Again, the community data shows the least bias and, importantly, the greatest consistency, suggesting that the bias is due to systematic error. This error could be due to undercatch as the community rain gauge is close to a small tree which may provide some sheltering. However, when compared to the nearby electronic rain gauge which is in an open position like the Dangila NMA rain gauge, bias is just 1.05, suggesting that the bias of ground observations in Fig. 7a is primarily due to spatial variability.

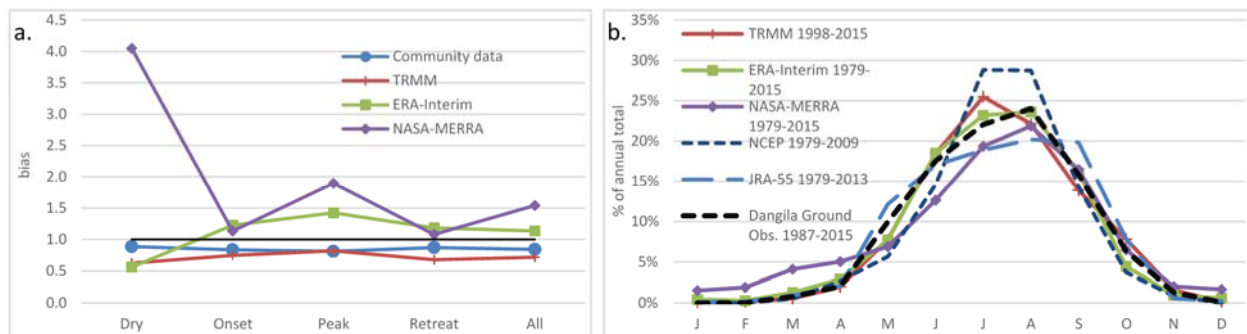


Fig. 7. Bias between daily rainfall from Dangila NMA rain gauge and alternative sources (a). Note that bias is computed as a ratio and the bold line at 1.0 represents zero bias. Median monthly rainfall totals as percentage of annual total for Dangila NMA rain gauge and gridded datasets (b).

Figs. 6 and 7 suggest that the gridded datasets perform poorly for this location, particularly in comparison to the community-based monitoring. To test whether the gridded datasets always perform poorly or solely for the period of overlap with the community data, the full available time series were analysed and monthly totals are considered in order to smooth out extreme events which reduce the PCC during daily rainfall analysis. When median monthly totals are normalised to annual total (Fig. 7b) the performance of the gridded datasets is improved. However, capturing the wet season peak still appears to be problematic which could have serious consequences for water resource assessment if these datasets were to be relied on in place of ground observations.

5. River flow

5.1 Formal observations

River flow data in Ethiopia is collected by the Ministry of Water, Irrigation and Electricity (MoWIE). It can be seen in Fig. 2 that two river gauges lie within Dangila *woreda* though the most useful for this project are named “Amen @ Dangila”, which is upstream of the community Kilti gauge, and “Kilti Nr Durbete”,

which is downstream of the community Kilti and Brante gauges and situated outside the *woreda*. Measurement of river stage at these locations is taken from depth gauge boards and the available time series spans 1988 to 2014 though with some significant gaps in the data lasting from months to years.

5.2 Community data

The two MoWIE monitored river gauges within Dangila *woreda* are located on ephemeral streams and it appears that either measurement does not always take place or monitoring records have not yet been completely digitised. A continuous time series of river stage measurements is therefore only available from the community-based monitoring programme. Following a decision taken by the community themselves, measurements take place twice a day as opposed to the daily formal river monitoring. In addition, with no external prompting, the community members who conduct the monitoring regularly add notes to their river stage records noting if a flood peak passed at a particular time and at what level. Such information is not available from formal sources.

The full time series of rainfall and river stage measurements collected by the Dangesheta community are presented in Fig. 8. It can be seen that the rivers are very flashy with sharp peaks in river stage quickly following rainfall events.

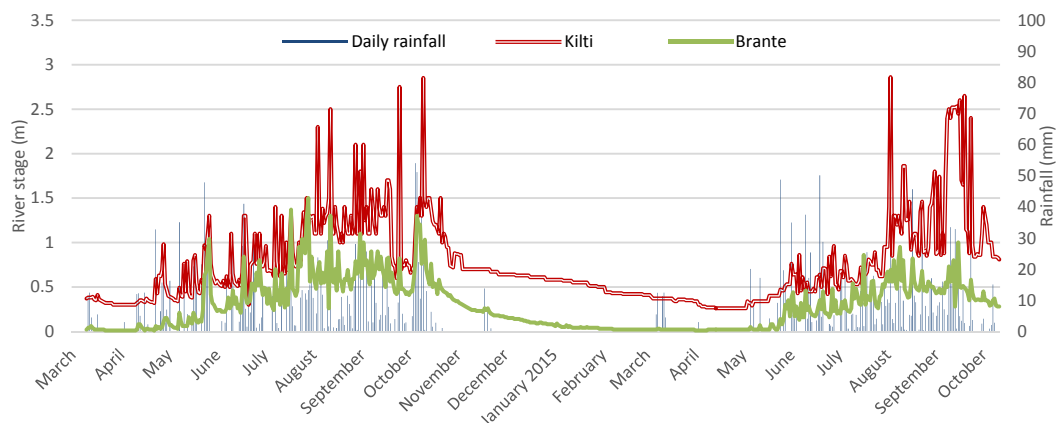


Fig. 8. Complete time series to date of daily Kilti and Brante river stage, and rainfall measurements from the community-based monitoring programme (2014-2015).

5.3 Performance of alternative river flow sources

A complete twice-daily record of river stage is held which is straightforward to cross-examine between rivers and with rainfall to determine if all peaks and troughs pass consistency tests. Suitable values for tolerance testing were derived from anecdotal and physical evidence obtained during field visits to the monitoring sites; such as the Kilti river's maximum peak in October 2014 which damaged the river gauge. Quality control procedures were passed for all of the community monitored river data.

Unfortunately there is only a very short period of overlap between the formal and the community river flow data. Therefore, correlations with formal sources are not considered the principal method of validating the river flow data. However, correlating the overlapping data between formal (Kilti and Amen) and community (Kilti and Brante) daily totals gives 0.52-0.58, similar to the correlation between the two formal river flow sources for their complete daily records, PCC = 0.58.

A unit runoff check involves dividing the (monthly) runoff by the catchment area in order to determine the runoff as a depth. This is compared for consistency with values obtained from nearby hydrologically similar catchments. This check is particularly useful in identifying abrupt changes in river flows resulting from river basin management activities (O'Donnell, 2012). Unit runoff checks were conducted for the Kilti and Brante flow measurements from the community-based monitoring programme and for the formal flow measurements for the Kilti and Amen (Fig. 9). The differences in unit runoff depths from the formal sources are increasingly significant from 1997 to 2001 and 2007 to 2010. This may be due to a period of unreliability of the rating curve and ongoing revision efforts which was the explanation given by MoWIE for considering the 2014 data to be unreliable (S. Mamo, personal communication, 10 December 2015). Thus, no conclusions should be drawn from the poor match with the community data during the 6-month overlap in 2014 (Fig. 9). It can be seen on the unit runoff check that there is a reasonable match between the two community monitored rivers, at least as good a match as has typically been seen between the two formally monitored rivers in previous years.

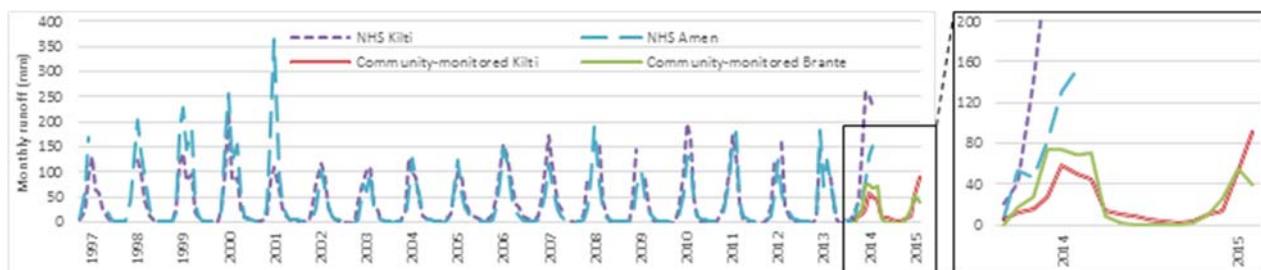


Fig. 9. Unit runoff checks for river flow data from community-based monitoring and formal sources. Gaps indicate insufficient flow measurements to calculate monthly totals. Note that the 2014 formal measurements are considered by MoWIE to be unreliable.

When river flows (daily totals) are correlated against rainfall from the NMA Dangila rain gauge, the PCCs are lower for all seasons and for all gauges (Fig. 10) than was achieved when validating rainfall and groundwater data. The low values reflect the geography and hydrogeology of the catchments where peak floods have been observed to occur with a very short time lag after the onset of a rainfall event. Very heavy overnight storms were experienced during fieldwork though when the rivers were visited early the following morning the river stage had already dropped from the level still visible on the banks to the level observed the previous day. Because rainfall measurements are cumulative and river stage measurements

are momentary, monitoring would have to be undertaken at a much higher frequency in order to achieve better correlations with rainfall. However, the PCCs in Fig. 10 are similar for both the formal and the community measurements particularly when all seasons are considered.

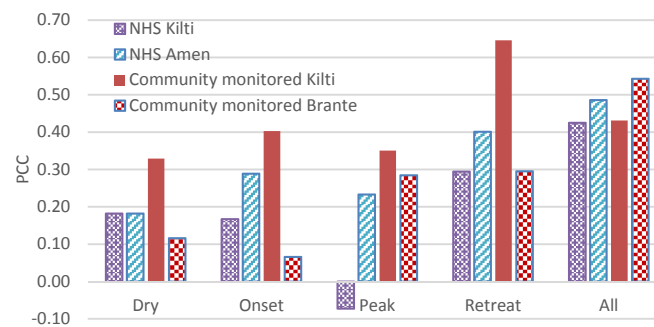


Fig. 10. Pearson correlation coefficient (PCC) between daily rainfall from Dangila NMA rain gauge and river flow measurements (daily totals) from formal and community sources. Note that “All” includes incomplete months excluded from other seasons explaining the contrast in relative PCC of, in particular community monitored Kilti, data from individual seasons to “All”.

6. Groundwater level data

6.1 Formal observations

The community monitored groundwater level data is the only means of accessing water table depth and recession anywhere within Dangila *woreda*. Extremely limited data on boreholes and groundwater are available from formal sources (see Supplementary Material).

6.2 Community data

It would be expected, given that the monitoring wells are in close proximity (maximum separation of 970 m), that groundwater levels from different wells would follow a similar pattern of seasonal variation. Peaks in water level during dry spells or plateaus spanning numerous rainfall events would suggest unreliable data. It is immediately obvious from Fig. 11 that the patterns in water level response are consistent, quality control procedures have been passed (with a single exception discussed below) and the validity of the data is confirmed when statistical comparisons are conducted between wells and with river stage.

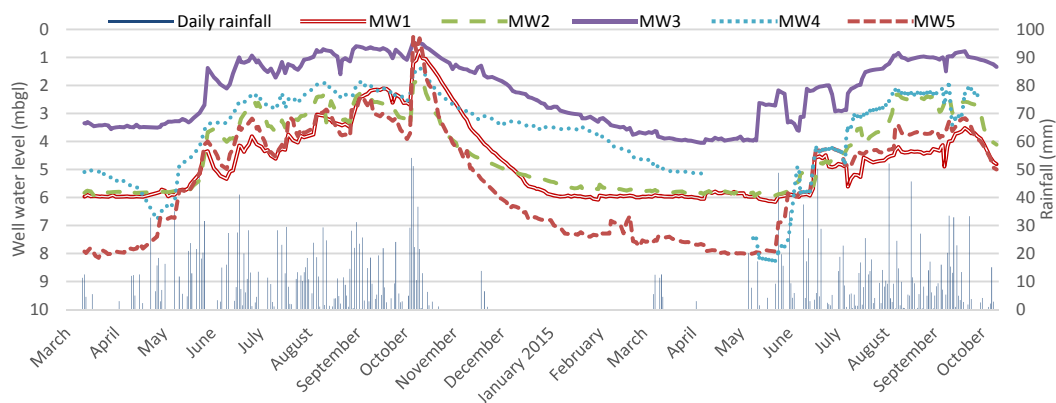


Fig. 11. Complete time series to date of groundwater level and rainfall measurements from the community-based monitoring programme (2014-2015).

Differences in amplification of water level responses to particular rainfall events have physical reasons: either due to features of the well itself, e.g. MW1 and MW5 peak the most significantly as they are open to direct precipitation and overland flow, or due to aquifer characteristics, e.g. MW4 declines the most gradually, proposed to be due to a lack of high-transmissivity layers, such as fractured bedrock within the shallow weathered regolith aquifer, which are present in other well bores (during workshop discussions the local community spoke of not striking rock when excavating MW4 unlike in other wells, particularly MW1 and MW5 where a rapid decline in water level is observed at the onset of the dry season). Analysis of the differences in well responses and discussions during community workshops have been invaluable in gaining a greater understanding of the shallow hydrogeology in the area.

6.3 Performance of alternative groundwater level sources

The quality control procedures had to be most carefully applied to the groundwater level data. Completeness tests showed occasional gaps of two days rather than the expected measurements every other day with some gaps of three days and one exceptional gap of eight days. It is noted that these larger gaps occur during the dry season when there is little groundwater level fluctuation and there are just as many measurements at a higher than required frequency on consecutive days. No groundwater level dataset was excluded for reasons of completeness. Consistency tests often highlighted errors where large “steps” in the data were present from one month of measurements to the next. Further investigations typically revealed that a spreadsheet had been labelled incorrectly and when the data was switched to the correct well the consistency test was passed. One such step in the data which failed according to spatial consistency (neighbouring wells do not show such a large drop at that time) and temporal consistency (such a large overnight drop has no physical explanation) has yet to be resolved and the excluded month can be seen in well MW4 on Fig. 11. Other than this single month of data for one particular well and

following some corrective reorganisation of datasets, the groundwater level data passes quality control procedures.

The groundwater level data cannot be validated against formal sources as no such data exists. Fig. 12 shows the Pearson correlation coefficient between water level responses of different monitoring wells. Bias is not applicable because the response of each well is expected to vary in absolute value; such variations are due to differing well and water table depths, variations in aquifer properties and differences in position on the groundwater flow path. Accordingly, precise agreement, i.e. correlations of 1, would not be expected. Indeed, it is the subtle differences in groundwater level response that are aiding understanding of the shallow hydrogeology of the area. Analysis was conducted for individual seasons and for the full time series.

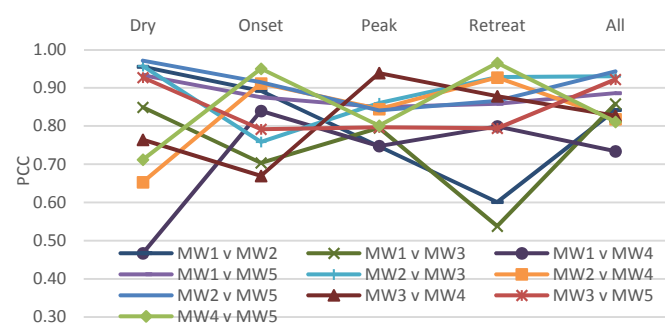


Fig. 12. Pearson correlation coefficient (PCC) between community monitored groundwater level data from monitoring wells MW1-5.

Fig. 12 shows that there is very good correlation between monitoring wells; the mean PCC between all wells for the full time series is 0.86. The raw data was investigated where the PCC is below 0.75 and in all cases a physical reason was apparent such as comparisons between wells during a period where one was predominantly dry (e.g. MW1 for long periods).

To further validate the groundwater level data, correlations were conducted with river stage from the two nearby community monitored gauges. River depth is being compared to depth to groundwater thus when river stage is high it would be expected that depth to the water table would be low and a perfect correlation would yield -1. However, the flashy response of the rivers to rainfall events and the lag until groundwater responds means it is unlikely that very close to -1 would be obtained but the results should still be high in the negative. The results of the correlations are presented in Table 1 and show highly satisfactory correlations with an average of -0.73.

Table 1. Pearson correlation coefficient (PCC) between community monitored river stage and groundwater level from monitoring wells MW1-5 for the entire time series

	Brante river stage vs;					Kilti river stage vs;				
Well:	MW1	MW2	MW3	MW4	MW5	MW1	MW2	MW3	MW4	MW5
PCC:	-0.75	-0.80	-0.76	-0.63	-0.83	-0.70	-0.76	-0.73	-0.64	-0.74

7. Discussion

7.1 Qualitative and quantitative value of community-based monitoring observations

The qualitative value of the community data is in contributing to the conceptual understanding of the shallow groundwater system. Conceptual understanding has only been possible with a combination of fieldwork and analysis of differences in well and river responses using data from the community-based monitoring programme. Slow declines in groundwater levels following rainfall events can indicate high storativity of the aquifer and significant river baseflow throughout the dry season can indicate an aquifer with the potential for exploitation.

The community data has quantitative value through providing complete time series spanning numerous seasons. For the purpose of understanding the shallow hydrogeological system to enable simulation of the impacts of increased abstraction, land use change, and climate variability; physically-based numerical models are being constructed using Shetran (Ewen et al., 2000) and GMS (Aquaveo, 2011). Construction and calibration of these necessarily transient models at scales useful for local management of water resources is only possible with the time series of river flow and groundwater level gathered by the community. Alongside traditional methods such as chloride mass balance (CMB), recharge assessments for the Dangeshta area are being conducted using the RIB model (Sun et al., 2013; Xu and van Tonder, 2001) and water table fluctuation method; neither of which would be possible without the time series of groundwater level. The close agreement of the community gathered and nearest formal rainfall dataset gives confidence that the formal rainfall dataset can be used in the models to extend the time series prior to the commencement of the community-based monitoring programme. Consistency of anomaly patterns as evidenced by the PCC between community gathered and gridded rainfall datasets enables selection of the most appropriate gridded dataset for infilling gaps in formal ground observation rainfall totals which occurred historically.

A key value of community-based monitoring programmes is the engagement of the local community, which, as the wider research programme progresses, will hopefully evolve to active management of their resources. The value to the local community has been expressed as a feeling of partnership in the project rather than constantly being subjects of research. Questions posed by the Dangeshta community during recent workshops involving the dissemination of findings demonstrated a level of engagement and an increase in hydrological knowledge that was not observed during workshops at the project onset.

Proffered reasons for differences between recession curves for groundwater levels from various wells, e.g. zones of aquifer with greater storage properties, have been incorporated into conceptual models. The community also speak of a sense of pride that their community are participating in the programme which may have implications beyond Dangesheta.

This research has shown that high quality hydrometeorological data for various applications can be collected by non-specialists from local communities. The data can reliably supplement that from formal sources or provide time series where no formal alternatives are available.

7.2 Recommendations for ensuring quality data production

The potential for community-based monitoring programmes to infill gaps in sparse, declining or non-existent formal monitoring networks is clear. However, there are numerous critical factors for ensuring quality data production. The early involvement of the local community is important to instil a sense of ownership of the equipment and the project. Assistance in site selection for monitoring points is an ideal way to engage the community early and was achieved in this case via the focus groups and participatory mapping workshops. Variations in well level responses indicate the monitoring wells were successfully identified to provide information on aquifer zones with varying potential for exploitation. Selection of the community members to be involved in the programme is particularly crucial. The completeness of these community datasets and their success in passing the WMO quality control standards indicates selection of monitoring personnel was successful in this case. Known and respected community members who live or work in close proximity to the monitoring points should be selected, if willing to participate, to ensure security of the equipment and to demonstrate to the community, simply by their involvement, that the programme has value. We are aware of community-based monitoring programmes in other areas of Ethiopia that have suffered issues such as vandalism of equipment (Zemadim et al., 2014) and falsification of data (D.L. Yiak, personal communication, 5 April 2015). In these cases monitoring or in-situ downloading of data has been conducted by outside (unknown to the community) people or a casually selected community member who may have been purely interested in the financial incentive. Notably, these examples were more equipment intensive and offered higher financial incentives than the Dangesheta case. Vandalism or data falsification have not been encountered during this study further confirming the value of community participation in site selection and nomination of community members to undertake the monitoring. The importance of feedback has been reported to us concerning Dangesheta and other examples of community-based monitoring programmes in Ethiopia: this could be delivered through visits and support as well as workshops presenting the collected data, eliciting from the community what the data reveals, explaining what the data is being used for, and giving the community the opportunity to ask questions, provide their own explanations for patterns in the data, and give suggestions for improving the

community-based monitoring programme. The continued performance of the community-based monitoring programme in generating high-quality observations is evidence of the value of the workshops.

7.3 Wider application of community-based hydrometeorological monitoring

It has been shown that community-based monitoring can be used to provide improved spatial density of measurements in areas of sparse and/or declining formal monitoring networks. In addition, where there exists relatively high densities of formal hydrometeorological monitoring points, community-based monitoring still has much to offer.

Gridded datasets are a viable alternative source of rainfall data in many regions though it has been shown here that over complex terrain with large differences in altitude gross over and under estimations of rainfall totals are possible, especially where grid size is large. Community-based monitoring can provide data of sufficient quality to add to the ground observation datasets used to calibrate and validate these gridded datasets.

8. Conclusions

The research shows that high-quality daily rainfall totals, sub-daily river stage and daily to sub-weekly groundwater level measurements are achievable by an astutely implemented and managed community-based monitoring programme. Formal rain gauge networks in many regions of the world are inadequately dense to provide confident interpolation of rainfall quantities. Gridded datasets with their necessarily low resolutions often cannot achieve good agreement with ground observations particularly in areas of spatial heterogeneity of intense convective precipitation and particularly when sub-monthly rainfall totals are required. Formal river monitoring networks are also insufficient with few available datasets for use in modelling catchments at less than the regional scale. Furthermore, formal river monitoring networks, along with formal rain gauge networks, are in decline as national institutions embark on cost-cutting practices; an issue which is particularly severe in less economically developed countries. In sub-Saharan Africa, groundwater level monitoring networks are essentially non-existent when it comes to shallow groundwater – the resource which is used by the majority of poor rural communities. It has been shown that community-based monitoring can provide high quality data to help fill these observational voids. Data screening for quality control indicates reliable and consistent measurements, as good as formal monitoring, can be obtained by local communities. Community-based monitoring can improve spatial and temporal characterisation of rainfall, river flow and groundwater level, reducing the uncertainty of using extrapolated/interpolated values from formal and gridded datasets or from modelling simulations. Statistical comparisons of the community-based monitoring data against formal sources and against other data simultaneously gathered by the local community validate their quality for use in further study. Our research has shown that benefits to the community include a greater understanding of their local

hydrology and hydrogeology, a sense of ownership of their water resources, and a sense of being a research partner as opposed to a subject. Such increased hydrological understanding in sub-Saharan Africa provides the basis for communities to manage their own resources which could increase food security by reducing reliance on rainfed agriculture.

9. Acknowledgements

David Walker is funded under the SAgE Faculty (Newcastle University Faculty of Science, Agriculture and Engineering) DTA programme. Fieldwork was supported by the Harry Collinson Travel Scholarship from Newcastle University and the Royal Geographical Society (with IBG) with a Dudley Stamp Memorial Award. The initial work setting up the community-based monitoring programme was funded by the NERC/DfID UpGro programme under Catalyst Grant NE/L002019/1. We are grateful for the co-operation of many people and organisations in Ethiopia, in particular; IWMI (International Water Management Institute), Bahir Dar University, and the local communities in and around Dangila *woreda*. We would also like to thank the anonymous reviewers for their useful comments and suggestions.

10. References

- Aquaveo, 2011. Groundwater Modelling System (GMS) Version 9.1, UT, USA.
- ATA, E., 2013. Realizing the Potential of Household Irrigation in Ethiopia. Working Strategy Document, Ethiopian Agricultural Transformation Agency.
- Beven, K., 1993. Prophecy, reality and uncertainty in distributed hydrological modelling. *Adv. Water Resour.*, 16(1): 41-51.
- Bonsor, H.C., MacDonald, A.M., 2011. An initial estimate of depth to groundwater across Africa. *British Geological Survey Open Report*, OR/11/067: 26pp.
- Burgos, A., Páez, R., Carmona, E., Rivas, H., 2013. A systems approach to modeling Community-Based Environmental Monitoring: a case of participatory water quality monitoring in rural Mexico. *Environ Monit Assess*, 185(12): 10297-10316. DOI:10.1007/s10661-013-3333-x
- Buytaert, W. et al., 2014. Citizen science in hydrology and water resources: opportunities for knowledge generation, ecosystem service management, and sustainable development. *Frontiers in Earth Science*, 2. DOI:10.3389/feart.2014.00026
- Cain, A., 2015. Water resource management under changing climate in Angola's coastal settlements, Presented during Special Session 10 at the World Water Congress XV (May 2015), Edinburgh, UK.
- Calow, R.C., MacDonald, A.M., Nicol, A.L., Robins, N.S., 2009. Ground Water Security and Drought in Africa: Linking Availability, Access, and Demand. *Ground Water*, 48(2): 246-256. DOI:10.1111/j.1745-6584.2009.00558.x

- Conners, D.E., Eggert, S., Keyes, J., Merrill, M.D., 2001. Community-based water quality monitoring by the Upper Oconee Watershed network. Proceedings of the 2001 Georgia Water Resources Conference (March 2001), University of Georgia, Athens, Georgia, USA.
- Conrad, C.C., Hilchey, K.G., 2011. A review of citizen science and community-based environmental monitoring: issues and opportunities. *Environ Monit Assess*, 176(1-4): 273-291.
DOI:10.1007/s10661-010-1582-5
- Conway, D. et al., 2009. Rainfall and water resources variability in sub-Saharan Africa during the twentieth century. *J. Hydrometeorol.*, 10(1): 41-59.
- CSA, 2008. Summary and statistical report of the 2007 population and housing census – population size by age and sex. Central Statistics Agency, Federal Democratic Republic of Ethiopia Population Census Commission, Addis Ababa.
- Dapaah-Siakwan, S., Gyau-Boakye, P., 2000. Hydrogeologic framework and borehole yields in Ghana. *Hydrogeol J*, 8(4): 405-416.
- Deutsch, W.G., Busby, A.L., Orprecio, J.L., Bago-Labis, J.P., Cequina, E.Y., 2005. Community-based hydrological and water quality assessments in Mindanao, Philippines. *Forests, Water and People in the Humid Tropics*. Cambridge University Press, Cambridge: 134-149.
- Dinku, T. et al., 2007. Validation of satellite rainfall products over East Africa's complex topography. *Int. J. Remote Sens.*, 28(7): 1503-1526.
- Dinku, T., Chidzambwa, S., Ceccato, P., Connor, S.J., Ropelewski, C.F., 2008. Validation of high-resolution satellite rainfall products over complex terrain. *Int. J. Remote Sens.*, 29(14): 4097-4110.
- Ebert, E.E., Janowiak, J.E., Kidd, C., 2007. Comparison of near-real-time precipitation estimates from satellite observations and numerical models. *Bulletin of the American Meteorological Society*, 88(1): 47-64.
- Evans, A.E.V., Giordano, M., Clayton, T., 2012. Investing in agricultural water management to benefit smallholder farmers in Ethiopia. AgWater Solutions Project country synthesis report. Colombo, Sri Lanka: International Water Management Institute (IWMI), (IWMI Working Paper 152): 35p.
- Ewen, J., Parkin, G., O'Connell, P.E., 2000. Shetran: distributed river basin flow and transport modeling system. *J. Hydrol. Eng.*, 5(3): 250-258. DOI:10.1061/(asce)1084-0699(2000)5:3(250)
- Fekete, B.M., Vörösmarty, C.J., Roads, J.O., Willmott, C.J., 2004. Uncertainties in precipitation and their impacts on runoff estimates. *Journal of Climate*, 17(2): 294-304.
- Garduño, H., Foster, S., 2010. Sustainable groundwater irrigation approaches to reconciling demand with resources. *GW-MATE Strategic Overview Series*, 4.
- Garduño, H., Foster, S., Raj, P., van Steenbergen, F., 2009. Addressing groundwater depletion through community-based management actions in the weathered Granitic basement aquifer of drought-prone Andhra Pradesh–India. *World Bank GW-MATE Case Profile Collection*, 19.

- Giordano, M., 2006. Agricultural groundwater use and rural livelihoods in sub-Saharan Africa: A first-cut assessment. *Hydrogeol J*, 14(3): 310-318. DOI:10.1007/s10040-005-0479-9
- Golding, B., Clark, P., May, B., 2005. The Boscastle flood: Meteorological analysis of the conditions leading to flooding on 16 August 2004. *Weather*, 60(8): 230-235.
- Gomani, M.C. et al., 2010. Establishment of a hydrological monitoring network in a tropical African catchment: An integrated participatory approach. *Physics and Chemistry of the Earth, Parts A/B/C*, 35(13–14): 648-656. DOI:<http://dx.doi.org/10.1016/j.pce.2010.07.025>
- Hochachka, W.M. et al., 2012. Data-intensive science applied to broad-scale citizen science. *Trends in Ecology & Evolution*, 27(2): 130-137. DOI:10.1016/j.tree.2011.11.006
- Huff, F.A., 1970. Sampling errors in measurement of mean precipitation. *Journal of Applied Meteorology*, 9(1): 35-44.
- Kongo, V.M., Kosgei, J.R., Jewitt, G.P.W., Lorentz, S.A., 2010. Establishment of a catchment monitoring network through a participatory approach in a rural community in South Africa. *Hydrol. Earth Syst. Sci.*, 14(12): 2507-2525. DOI:10.5194/hess-14-2507-2010
- Kundzewicz, Z.W., 1997. Water resources for sustainable development. *Hydrological Sciences Journal*, 42(4): 467-480. DOI:10.1080/02626669709492047
- Lapworth, D.J. et al., 2013. Residence times of shallow groundwater in West Africa: implications for hydrogeology and resilience to future changes in climate. *Hydrogeol J*, 21(3): 673-686. DOI:10.1007/s10040-012-0925-4
- Legates, D.R., Willmott, C.J., 1990. Mean seasonal and spatial variability in gauge-corrected, global precipitation. *Int. J. Climatol.*, 10(2): 111-127.
- Liu, B.M. et al., 2008. Overcoming limited information through participatory watershed management: Case study in Amhara, Ethiopia. *Physics and Chemistry of the Earth, Parts A/B/C*, 33(1–2): 13-21. DOI:<http://dx.doi.org/10.1016/j.pce.2007.04.017>
- MacDonald, A.M., Calow, R.C., MacDonald, D.M.J., Darling, W.G., Dochartaigh, B.E.O., 2009. What impact will climate change have on rural groundwater supplies in Africa? *Hydrol. Sci. J.-J. Sci. Hydrol.*, 54(4): 690-703. DOI:10.1623/hysj.54.4.690
- Maidment, R.I. et al., 2014. The 30 year TAMSAT African Rainfall Climatology And Time series (TARCAT) data set. *Journal of Geophysical Research: Atmospheres*, 119(18): 10,619-10,644.
- Martin, N., Van De Giesen, N., 2005. Spatial distribution of groundwater production and development potential in the Volta River basin of Ghana and Burkina Faso. *Water International*, 30(2): 239-249.
- Motovilov, Y.G., Gottschalk, L., Engeland, K., Rodhe, A., 1999. Validation of a distributed hydrological model against spatial observations. *Agricultural and Forest Meteorology*, 98: 257-277.

- Namara, R.E. et al., 2011. Smallholder shallow groundwater irrigation development in the upper east region of Ghana. Colombo, Sri Lanka: International Water Management Institute (IWMI), (IWMI Working Paper 143): 35p.
- Nature, 2015. Rise of the citizen scientist. [Editorial 18-8-15].
- New, M., Todd, M., Hulme, M., Jones, P., 2001. Precipitation measurements and trends in the twentieth century. *Int. J. Climatol.*, 21(15): 1889-1922.
- Nicholson, S.E., 2001. Climatic and environmental change in Africa during the last two centuries. *Clim. Res.*, 17(2): 123-144. DOI:10.3354/cr017123
- Nicholson, S.E. et al., 2003. Validation of TRMM and Other Rainfall Estimates with a High-Density Gauge Dataset for West Africa. Part II: Validation of TRMM Rainfall Products. *Journal of Applied Meteorology*, 42(10): 1355-1368. DOI:10.1175/1520-0450(2003)042<1355:VOTAOR>2.0.CO;2
- O'Donnell, G.M., 2012. Technical Note On Data Quality Control, Infilling and Record Extension (Unpublished), NBI Water Resources Planning and Management Project, Nile Basin Decision Support System (DSS).
- Owor, M., Taylor, R.G., Tindimugaya, C., Mwesigwa, D., 2009. Rainfall intensity and groundwater recharge: empirical evidence from the Upper Nile Basin. *Environ. Res. Lett.*, 4(3): 6. DOI:10.1088/1748-9326/4/3/035009
- Pavelic, P., Giordano, M., Keraita, B., Ramesh, V., Rao, T., 2012. Groundwater availability and use in Sub-Saharan Africa: a review of 15 countries. Colombo, Sri Lanka: International Water Management Institute (IWMI): 274p.
- Pavelic, P., Villholth, K.G., Shu, Y.Q., Rebelo, L.M., Smakhtin, V., 2013. Smallholder groundwater irrigation in Sub-Saharan Africa: country-level estimates of development potential. *Water International*, 38(4): 392-407. DOI:10.1080/02508060.2013.819601
- Pegram, G., Bardossy, A., 2013. Downscaling Regional Circulation Model rainfall to gauge sites using recorrelation and circulation pattern dependent quantile-quantile transforms for quantifying climate change. *J. Hydrol.*, 504: 142-159. DOI:10.1016/j.jhydrol.2013.09.014
- Peterson, T.C. et al., 1998. Homogeneity adjustments of in situ atmospheric climate data: A review. *Int. J. Climatol.*, 18(13): 1493-1517. DOI:10.1002/(sici)1097-0088(19981115)18:13<1493::aid-joc329>3.0.co;2-t
- Refsgaard, J.C., Knudsen, J., 1996. Operational validation and intercomparison of different types of hydrological models. *Water Resour. Res.*, 32(7): 2189-2202.
- Ridder, D., Pahl-Wostl, C., 2005. Participatory Integrated Assessment in local level planning. *Reg Environ Change*, 5(4): 188-196. DOI:10.1007/s10113-004-0089-4

- Robins, N.S., Davies, J., Farr, J.L., Calow, R.C., 2006. The changing role of hydrogeology in semi-arid southern and eastern Africa. *Hydrogeol J*, 14(8): 1483-1492.
DOI:<http://dx.doi.org/10.1007/s10040-006-0056-x>
- Robinson, M. et al., 2000. Evolving improvements to TRMM ground validation rainfall estimates. *Physics and Chemistry of the Earth, Part B: Hydrology, Oceans and Atmosphere*, 25(10–12): 971-976.
DOI:[http://dx.doi.org/10.1016/S1464-1909\(00\)00135-0](http://dx.doi.org/10.1016/S1464-1909(00)00135-0)
- Rossiter, D.G., Liu, J., Carlisle, S., Zhu, A.X., 2015. Can citizen science assist digital soil mapping? *Geoderma*, 259–260: 71-80. DOI:<http://dx.doi.org/10.1016/j.geoderma.2015.05.006>
- Roy, H.E. et al., 2012. Understanding citizen science and environmental monitoring. Final report on behalf of UK Environmental Observation Framework. NERC Centre for Ecology and Hydrology and Natural History Museum.
- Sullivan, B.L. et al., 2009. eBird: A citizen-based bird observation network in the biological sciences. *Biological Conservation*, 142(10): 2282-2292. DOI:10.1016/j.biocon.2009.05.006
- Sun, X. et al., 2013. Application of the rainfall infiltration breakthrough (RIB) model for groundwater recharge estimation in west coastal South Africa. *Water SA*, 39(2): 221-230.
DOI:10.4314/wsa.v39i2.5
- Symeonakis, E., Bonifácio, R., Drake, N., 2009. A comparison of rainfall estimation techniques for sub-Saharan Africa. *Int. J. Appl. Earth Obs. Geoinf.*, 11(1): 15-26.
- Taylor, R.G., Koussis, A.D., Tindimugaya, C., 2009. Groundwater and climate in Africa—a review. *Hydrological Sciences Journal*, 54(4): 655-664.
- Tourian, M.J., Sneeuw, N., Bardossy, A., 2013. A quantile function approach to discharge estimation from satellite altimetry (ENVISAT). *Water Resour. Res.*, 49(7): 4174-4186. DOI:10.1002/wrcr.20348
- Vianna, G.M.S., Meekan, M.G., Bornovski, T.H., Meeuwig, J.J., 2014. Acoustic Telemetry Validates a Citizen Science Approach for Monitoring Sharks on Coral Reefs. *PLoS ONE*, 9(4): e95565.
DOI:10.1371/journal.pone.0095565
- Washington, R., Harrison, M., Conway, D., Black, E., 2004. African climate report: a report commissioned by the UK Government to review African climate science, policy and options for action. Department for Environment, Food and Rural Affairs.
- Washington, R. et al., 2006. African Climate Change: Taking the Shorter Route. *Bulletin of the American Meteorological Society*, 87(10): 1355-1366. DOI:10.1175/BAMS-87-10-1355
- Willmott, C.J., Robeson, S.M., Feddema, J.J., 1994. Estimating continental and terrestrial precipitation averages from raingauge networks. *Int. J. Climatol.*, 14: 403-414.
- WMO, 2003. Twenty-first status report on implementation of the World Weather Watch: Forty years of World Weather Watch, Report 957, World Meteorological Organization (WMO), Geneva, Switzerland.

- WMO, 2011. Guide to Climatological Practices, WMO-No. 100, World Meteorological Organisation (WMO), Geneva, Switzerland.
- Wolff, D.B. et al., 2005. Ground Validation for the Tropical Rainfall Measuring Mission (TRMM). *Journal of Atmospheric and Oceanic Technology*, 22(4): 365-380. DOI:10.1175/JTECH1700.1
- Woodroffe, A., 1988. Summary of weather pattern development of the storm of 15/16 October 1987. *Meteorological Magazine*, 117(1389): 99-103.
- Xu, Y., van Tonder, G.J., 2001. Estimation of recharge using a revised CRD method. *Water SA*, 27(3): 341-343.
- Zemadim, B., McCartney, M., Langan, S., Sharma, B., 2014. A participatory approach for hydrometeorological monitoring in the Blue Nile river basin of Ethiopia. Colombo, Sri Lanka: International Water Management Institute (IWMI), (IWMI Research Report 155): 32p.